Feature Extraction and Classification of Clouds in High Resolution Panchromatic Satellite Imagery

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Abstract — **The detection of vessels in high resolution panchromatic satellite imagery is of high interest to the Navy. A sophisticated software known as the Rapid Image Exploitation Resource (RAPIER®) was developed by engineers at the Space and Naval Warfare Systems Center Pacific (SSC PAC) [1][2][3]. RAPIER® is capable of detecting ships in satellite imagery by masking out land, searching for anomalies in the ocean, and reporting the detects as possible ship objects. However, if the image contains a high percentage of cloud coverage, a high number of false positives are triggered by the clouds. The work presented explores feature extraction methods to accurately distinguish clouds from ship objects in order to reduce the software false alarm rate.**

Keywords—satellite imagery; cloud detection; machine intelligence; image processing; RAPIER;

I. INTRODUCTION

In the defense community, software has been developed to detect and classify vessels in high resolution panchromatic satellite imagery. At SSC PAC, a group of engineers have developed sophisticated software to search for objects of interest in satellite imagery. This software framework is called RAPIER®, the Rapid Image Exploitation Resource.

RAPIER® is capable of processing synthetic aperture radar (SAR) and panchromatic (visible spectrum imagery) satellite imagery and searches for objects of interest; specifically ships in a maritime environment. This is achieved by masking out land and searching for anomalies on the open ocean. The detections are saved as image chips, and are loaded into HyperText Markup Language (HTML) and Keyhole Markup Language (KML) files for the user to view.

One of the limitations of RAPIER® occurs when processing panchromatic imagery from sensors such as Quickbird2, IKONOS, and Worldview 1 and 2. A high presence of clouds is captured from these sensors, a problem not experienced in SAR imagery. SAR imagers have the ability to penetrate through clouds, which captures data in the microwave and electromagnetic spectrum [4].

The presence of clouds in an image can be triggered by RAPIER® as an anomaly when processing panchromatic imagery. This causes the software to report detects at a high false alarm rate and increases processing time. The focus of this paper is to explore methods accurately distinguish clouds from ships in high resolution panchromatic imagery. This is done by examining various feature extraction methods.

II. RELATED RESEARCH

Texture is one of most unique features of a cloud, and can be used to distinguish it from ship objects. Several researchers have explored cloud textural analysis as a method to perform cloud type classification on lower resolution satellite imagery, such as Advanced Very High Resolution Radiometer (AVHRR) or other meteorological satellite imagery [5][6]. Textural analysis techniques such as Gabor wavelets and Grey Level Co-Occurrences Matrices methods were performed by these researchers. The work presented in this paper will explore the applicability of these techniques to higher resolution imagery such as those captured by IKONOS, QuickBird 2, and Worldview 1 and 2 for the purpose of distinguishing ships from clouds.

In 2011, engineers from Tomnod Inc. were contracted by SSC PAC to research various cloud feature extraction methods to reduce the false alarm rate of RAPIER®. Their approach was to take image chips produced by RAPIER®, and classify the results into one of the four categories: ship, cloud, fast moving ship, and other, as shown in Fig. 1. Their research results are summarized in [7]. The paper focuses on two aspects: extracting features and applying supervised classification on these features. The feature extraction techniques discussed in the paper include Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Features (SURF), Histogram of Oriented Gradients (HOG), texture-based features, and ship-specific features [7]. Our research will explore alternative feature extraction methods to achieve better classification accuracy.

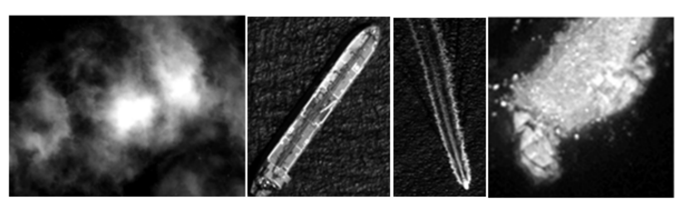

Fig. 1. Dataset separated by the following four classes (left to right): cloud, ship, fast moving ship, and other.

III. FEATURE EXTRACTION

A. *Texture Analysis*

The textures of cloud versus ship images are visibly different from one another. Therefore, by quantifying the image textures using computer vision texture extraction methods, we can use these measures as feature descriptors for our classifier.

The Gabor wavelet filter can be used to extract texture information from an image. The 2D Gabor wavelet ψ(x,y) is defined by the equations listed below [8].

$$\psi(x, y; f, \theta) = \frac{f^2}{\pi\gamma} e^{-\left(\frac{f^2}{\gamma^2} x'^2 + \frac{f^2}{2} y'^2\right)} e^{-i2\pi f x'} \quad (1)$$

$$x' = x\cos\theta + y\sin\theta,$$

$$y' = -x\sin\theta + y\cos\theta.$$

In the equations above, f is the frequency of the sinusoidal plane, θ is the clockwise rotation of the Gaussian envelope, γ is the spatial width of the filter alone the plane wave, and □ is the spatial width perpendicular to the wave.

In the experiments that we have conducted, θ varies from $0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}$, and the sinusoidal plane frequency f varies from $\frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \frac{1}{16}$. The set of 16 Gabor filters are applied to a sample ship and cloud image, shown below in Fig. 2 and Fig. 3. The extracted features in these two images show distinct differences. The sample filtered ship image appears to have more extracted objects using the various filter frequency values. However, the sample filtered cloud image appears to have extracted cloud contours only at the higher frequency values.

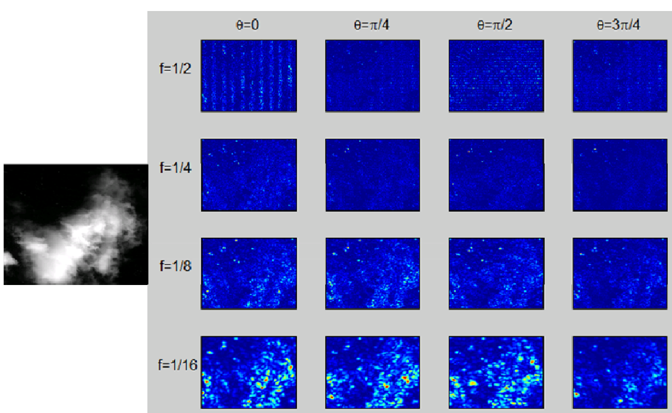

Fig. 2. Sample cloud image and Gabor convolved images at various frequency and orientation.

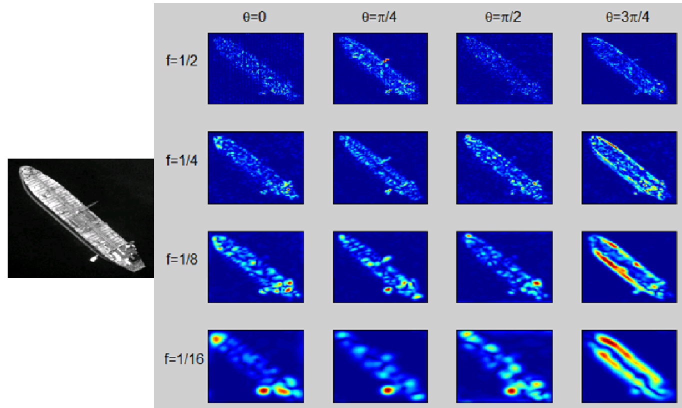

Fig. 3. Sample ship image and Gabor convolved images at various frequency and orientation.

For every wavelet angle θ, we compute the normalized correlation coefficient C, defined below, for various combinations of frequency values. T(x,y) represents the template image, and I(x,y) represents the test image.

$$C(x, y) = \frac{\sum_{x',y'}\left[T(x',y')\cdot I(x+x',y+y')\right]^2}{\sqrt{\sum_{x',y'} T(x',y')^2 \cdot \sum_{x',y'} I(x+x',y+x')^2}} \quad (2)$$

The following wavelet frequency combinations listed below are computed for f. Their correlation coefficients are computed amongst their corresponding filtered images. This will give us 20 correlation coefficient values, which we will use as part of our feature vector.

f = 1/2 vs. 1/4
f = 1/2 vs. 1/16
f = 1/4 vs. 1/8
f = 1/4 vs. 1/16
f = 1/8 vs. 1/16

We anticipate the correlation values computed from the ship images will be higher than those calculated from the cloud images. The high correlation values are a result of high amounts of texture extracted from both low and high frequencies of the images. Since cloud contours were only extracted in the higher frequency values of the filtered images, the correlation will be lower. This allows us to separate the two classes.

B. *Line Detection using Hough Transform*

A distinguishing feature of a ship is its shape. The sides of a ship form straight edges. In computer vision, these edges can be identified using the Hough transform. The unique shape of a ship can be used to distinguish it from a cloud object. If we can accurately identify two long parallel lines in our image, we can pre-label that image as containing a ship.

The Hough transform is a feature extraction technique that is used to identify line segments in an image [9]. This method processes a binary edge image as an input, and extracts line segments that meet a certain pixel length threshold. An example of a detected Hough line segment is shown in Fig. 4 and Fig. 5. These figures display the edge map for a sample ship and cloud image and their detected lines using the Hough transform. The Matlab implementation of the Canny edge detector was used with ideal thresholds selected by the software and sigma set at $\sqrt{2}$. An alternative edge extraction technique will be discussed in the following wavelet section.

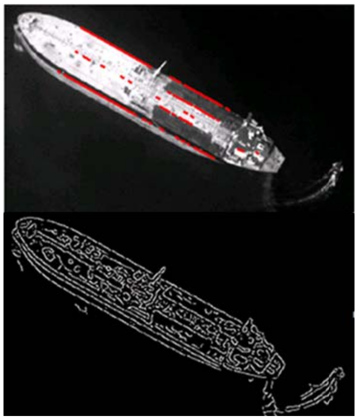

Fig. 4. Lines detected from sample ship image (top) extracted from Canny edge image (bottom).

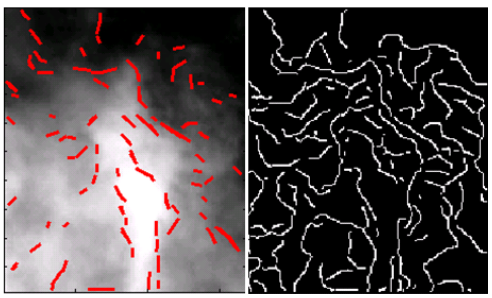

Fig. 5. Lines detected from sample cloud image (left) extracted from Canny edge image (right).

C. Wavelet Edge Detection

In conditions of high sea state, traditional edge detectors such as Canny, Sobel, and Prewitt are too sensitive to background noise. It becomes difficult to extract edges of a ship using these traditional methods, as shown in Fig. 6. Therefore, we explored nontraditional edge detection methods using wavelet decomposition to suppress background noise.

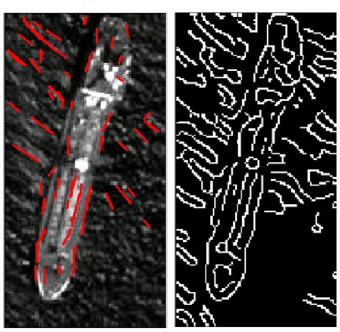

Fig. 6. Example where Hough transform line detection fails to identify parallel line segments containing a ship image.

A three level wavelet decomposition structural representation is shown below in Fig. 7. For each level, the high frequency detail sub-band images HL, LH, and HH are used. These images are computed using a combination of highpass and lowpass filtering. They extract horizontal, vertical, and diagonal details respectively.

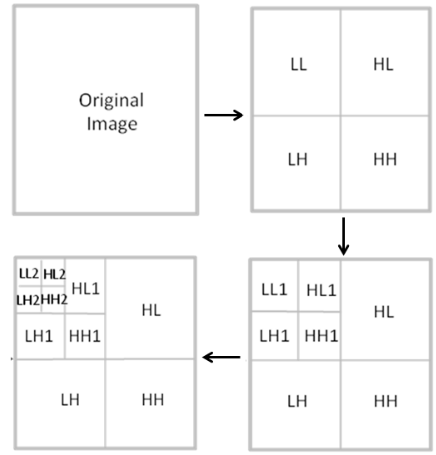

Fig. 7. Structure for wavelet decomposition.

For each processed image chip, the image is rotated such that the major axis of the detected object is oriented horizontally. An example is shown below in Fig. 8.

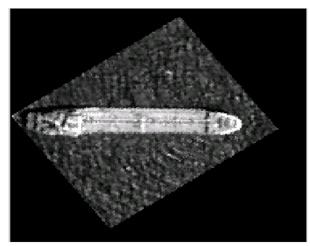

Fig. 8. Image rotated such that the detected object major axis is oriented horizontally.

A level three image decomposition using Haar wavelet approach was taken to emphasize horizontal details while performing noise suppression. Once the image is decomposed, the high frequency detail components of the image (HL, LH, and HH) are multiplied with a factor α_1, α_2, α_3 (where $\alpha_1 > \alpha_2$ and $\alpha_1 > \alpha_3$), and the image is reconstructed. The α_1 scaling factor is for the horizontal detail, α_2 is for the diagonal detail, and α_3 is for the vertical detail component. The image is then reconstructed containing emphasis on the horizontal detail component. A traditional edge detector can then be applied to the reconstructed image to obtain a noise suppressed edge image. A sample experimental result is shown below in Fig. 9.

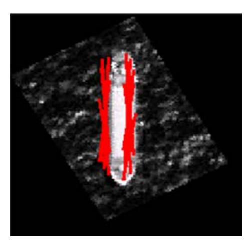

Fig. 9. Detected lines using the Hough transform on a wavelet filtered image.

D. System Flow Diagram

A final algorithm was developed to classify ship objects from clouds using the feature extraction methods described in the previous sections. This algorithm is summarized in the flow diagram in Fig. 10. The method requires that edge detection is performed using both Canny and Haar wavelets. Parallel line detection using Hough transform is performed on both edge images, and the image under test is either labeled as containing ships or further processing is done. If further processing is needed, the Gabor wavelets are used to analyze the texture of the image, and correlation coefficients among the frequency combinations of the filtered images are calculated. These 20 features are then supplied to a classifier to determine the image class.

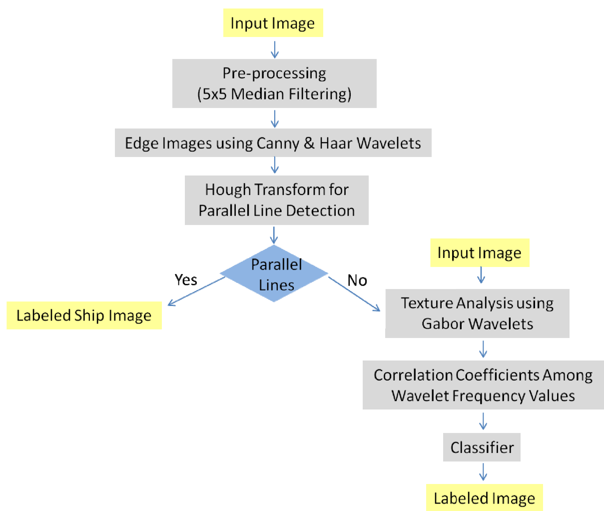

Fig. 10. Flow diagram of the finalized cloud filtering algorithm.

IV. RESULTS

The dataset is made up of 3709 grayscale images, and is separated into the following four classes: cloud, ship, fast moving ship, and other. Examples from each of these classes are shown below in Fig. 1. There are 1037 cloud images, 770 ship images, 487 fast moving ship images, and 1415 images classified as other. The first two classes, cloud and ship, will be used for our research, however, results reported in [7] use all four classes.

Distinguishing small vessels and small popcorn clouds is an extremely challenging task, even for a human observer. Therefore, the dataset is pre-filtered to contain only large objects. The final dataset consists of 955 cloud images and 452 ship images.

The SVM classifier was used to train and test the dataset. The training set consists of 200 ship and 200 cloud images, which were randomly selected from the dataset. The remaining images were used for testing. For each experimental test, 10 iterations are performed, and the mean classification accuracy and standard deviation is calculated. The first test only uses the 20 correlation coefficients from the Gabor filtered images as features. A mean classification accuracy of 94.12% with a standard deviation of 0.81 was achieved. A second test was performed, which uses the Hough transform to pre-filter the dataset. The features consist of the 20 correlation coefficients, maximum line length detected, and standard deviation of the line angles detected. A mean classification accuracy of 97.86% was achieved with a standard deviation of 0.32.

V. CONCLUSIONS

We have presented a method to accurately identify cloud objects in high resolution panchromatic satellite imagery based on a combination of feature extraction techniques. A simplified version of the algorithm discussed has been implemented within RAPIER® and has dramatically reduced the software false alarm rate produced by clouds. Further research involves identifying ship objects obscured by clouds, such as the example shown in Fig. 11.

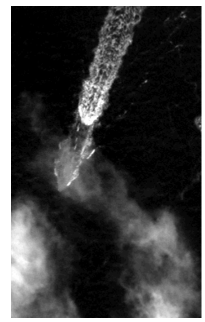

Fig. 11. Example of ship objects obscured by clouds.

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